The Impact of Hurricane Katrina on Income Inequality: A Synthetic Control Analysis

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Abstract

Hurricane Katrina devastated the state of Louisiana in 2005. Using the synthetic control method, we evaluate the effect of this disaster on income inequality in Louisiana. The findings suggest that the disaster has an inequality-increasing impact on the income shares of the top 0.1% and top 1% of income earners in the immediate year following its occurrence. We find evidence of heterogeneous effects of the disaster among income earners on the top decile. The effect of the disaster is positive and statistically significant for the top 1% income share, but it is negative and insignificant for the income shares of the next 9%. Our empirical exercise also indicates that the effect from the first year is not persistent and evolves into a highly volatile pattern in the medium-term. We also find that Hurricane Katrina has a negligible effect on inequality in the long-term. Our results are robust to various specification checks and to the inclusion of a rich set of inequality measures.

Keywords: Inequality, Natural Disasters, Katrina, Top income shares
JEL codes: O51, D63, R11, Q54

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1 Introduction

How do catastrophic natural disasters affect income inequality? This question is of utmost interest for social scientists given the recent rise in income disparities through the developed world, coupled with an increase in natural disasters due to the current climate crisis. Few studies have tried to explore the relationship between natural disasters and income inequality using either cross country comparisons (for example, Yamamura, 2015) or within country variations (for example, Miljkovic and Miljkovic, 2014; Pleninger, 2020). The current body of evidence is far from conclusive due to the methodological complexities of measuring income inequality in areas devastated by natural catastrophes; the difficulties of implementing econometric methods that can properly estimate causal effects, and also because the effect of large catastrophic events may be different than the effect of events with lesser destruction.

This paper focuses on the case of Hurricane Katrina, one of the deadliest natural disasters to ever hit the United States. The most affected state was Louisiana having a death-toll of more than 1,800 people. Apart from the loss of life, the hurricane destroyed around 300,000 homes, and led to displacement of nearly 770,000 individuals.[1][2] This type of natural disasters could have long-lasting impacts on people's live and may lead to general changes in the economy. Precise state-level income inequality data exists for the United States, which facilitates the study of our relationship of interest.

We explore the relationship between Hurricane Katrina and income inequality using the synthetic control method for quantitative case studies developed by Abadie and Gardeazabal (2003). This methodology creates a statistical synthetic control that simulates what would have happened to an observed treated unit in the absence of treatment.[3] In our case, we create a synthetic Louisiana in the form of a weighted average of states that were not affected by hurricane Katrina selected based on terms of trends of the inequality measure, income per capita, and other economic and demographic characteristics that we use as predictors. Then, the differences in inequality between the actual Louisiana and the synthetic control in the post-Katrina period can be attributed to the natural disaster. After that, we perform various robustness tests and sensitivity analyses to verify the validity of our findings.

We use four baseline measures to measure inequality: the top 0.1% and top 1% income shares, the next top 9%, and the dispersion ratio between the top 1% and the next 9%.[4] Our findings indicate that Hurricane Katrina had an inequality-increasing effect in 2006, the first year after the disaster. However, these results become less clear in the following years. From 2007 to 2013, we observe high levels of volatility in our baseline inequality measures. Then, by 2014 and 2015, the last years covered in this study, the differences between actual and synthetic Louisiana vanish. This suggests that Hurricane Katrina had null long-term effects on inequality. As a robustness check, we investigate the relationship between Katrina and ten alternative inequality measures including the top 10% and top 5% income shares, the dispersion ratio between the top 10% and the bottom 90%, the Gini coefficient, and other inequality measures. We find that in general Katrina had a

[1]US Census Bureau, "Hurricane Katrina 10th Anniversary: Aug. 29", https://www.census.gov/newsroom/facts-for-features/2015/cb15-ff16.html, accessed May 17, 2021.

[2]The White House of President George W. Bush, "Chapter One: Katrina in Perspective." https://georgewbush-whitehouse.archives.gov/reports/katrina-lessons-learned/chapter1.html, accessed May 17, 2021.

[3]For a recent and detailed description of the synthetic control method, refer to Abadie (2021).

[4]The bottom nine percentiles of the top decile (P90-P99) is known as the next 9%.

positive short run effect in income inequality using the alternative measures; however, again, this effect is not everlasting.

This paper relates to the literature linking natural disasters with income inequality. We contribute to this literature by estimating the treatment effect of Hurricane Katrina, one of the major disasters to ever hit the United States, in a large number of inequality measures using a novel estimation strategy as the synthetic control method. Majority of the existing studies that link natural disasters with inequality use the Gini coefficient as their main inequality measurement.[5] In this study, we use the income shares earned by the top of the income distribution and dispersion rates as our main inequality measures. These measures let us explore what happens at the very top income group and disentangle the distributional effect of Hurricane Katrina.

This study also contributes to the literature that investigates the economic impact of Hurricane Katrina. Various studies have shown the effects that the hurricane had on the local economy, income, inequality, and social capital (see Ewing et al., 2007; Deryugina et al., 2018; Shaughnessy et al., 2010; Hawkins and Maurer, 2010; Wang and Ganapati, 2018). Shaughnessy et al. (2010) study the impact of Hurricane Katrina on income distributions immediately and two years after the hurricane. The authors find that the disaster had inequality-decreasing effects in the city of New Orleans. Focusing on the whole state of Louisiana, our findings contrast with those of Shaughnessy et al. (2010). We find inequality-increasing effects in the short run and a null-effects in the long run using a richer set of inequality measures. Furthermore, unlike previous studies, we carefully estimate a causal effect of the hurricane on inequality.

The outline of the rest of this papers is as follows: Section 2 is the background where we briefly delineate the economic impact of hurricane Katrina. Section 3 provides the conceptual framework, briefly refers to the existing literature of inequality and natural disasters, and develops the main hypotheses of this study. Section 4 explains the data and the variables used in our empirical exercise. Section 5 describes the methodology and statistical inference. Section 6 presents the main results and robustness checks. Section 7 concludes this paper.

2 Background

Hurricane Katrina came ashore in southern Louisiana on August 29, 2005. With more than 1,800 deaths in its wake, this devastating force of nature has been one of the deadliest single natural disasters to ever hit the United States. Aside from the significant loss of life, Hurricane Katrina led to the displacement of 770,000 people and destroyed or made uninhabitable 300,000 housing units, ultimately leaving thousands of people homeless.[6] From an economic perspective, Katrina caused enormous destruction adding up to damages of more than 172 billion US Dollar.[7] In Louisiana, the production levels of fundamentally important goods such as oil, gas, sugar, seafood, and chemicals were substantially reduced, causing several hundreds of millions of US Dollar worth of damage

[5] There are some exceptions, for example see Pleninger (2020)

[6] According to official information from the White House and the Government Accountability Office available at https://georgewbush-whitehouse.archives.gov/reports/katrina-lessons-learned/chapter1.html and https://www.gao.gov/assets/gao-09-81.pdf, accessed May 17, 2021.

[7] The cost value is adjusted for inflation and expressed in 2021 US Dollars. In 2005, the cost estimation was 150 billion USD.

and ending in dramatic price spikes for refined products.[8] Until today, it has been the costliest tropical storm to have struck the United States.

When a hurricane of higher category strikes and makes landfall, it has the potential to affect large numbers of people, leaving an obvious path of destruction. Individuals or cities, however, may be impacted to varying degrees. For example, as an immediate consequence of Hurricane Katrina, around 80% of New Orleans (LA) was flooded as levees designed to cope with hurricanes up to category three began to break and leak. It is documented that the worst flooding occurred in the city's 9th ward, an area that is largely uninsured and characterized by lower income opportunities (Amadeo, 2018). The ability of individuals or households to evacuate before the hurricane hits as well as their ability to return to the destroyed area for rebuilding homes and businesses varies depending on wealth and income. Pastor et al. (2006) argue that natural disasters and rescues do not have egalitarian effects but instead impose disproportionate environmental injustice to more vulnerable groups at the lower income levels. Analyzing the effects of Hurricane Katrina, Landry et al. (2007) find evidence that higher income households are more likely to migrate back home in the months immediately following this devastating natural event due to superior endowment of monetary resources. Using data at the country-level, Kahn (2005) shows that economies with more equal distributions of income suffer fewer deaths from disasters. Whereas Hurricane Katrina induced sharp disruptions to Louisiana's local economy, business structures, population, and workforce, the varying intensity to which individuals or households of different income levels were affected by the storm has not only considerably changed the state's economic, political, and social environment, but also its income distribution and income inequality levels.

Given this, understanding Hurricane Katrina's impact on the income distribution is of critical importance. There is need for political decisionmakers to estimate differentiating income distribution effects from disaster-driven fluctuations and from other impact factors. Using a novel method, our study is the first to employ a rich set of inequality measures related to the income distribution and income inequality levels, trying to investigate short-term inequality shocks in the aftermaths of Hurricane Katrina, and potential long-term convergence back to a stable path.

3 Theory, literature review, and hypotheses

3.1 Framework and literature review

The income inequality literature provides two competing and contrasting economic theories, leaving the effects of natural disasters on income distribution ex ante ambiguous. According to the *vulnerability argument*, income inequality is expected to widen in the wake of natural disasters. It states that the economically less privileged individuals and people without property ownership are more vulnerable as they are more likely to experience losing their jobs, being injured, having to be evacuated and displaced, and paying higher rents due to reduced housing stock (Howell and Elliott, 2019; Yamamura, 2015). For this group, each of these risks imposes a critical financial liability. Even with the presence of safety nets such as insurance risk and cost coverage or disaster-related aid programmes, it may take years for people further down the income distribution to

[8] According to the White House and the Department of Energy available https://www.energy.gov/fe/services/petroleum-reserves/strategic-petroleum-reserve/releasing-oil-spr, accessed May 17, 2021.

recover from a natural disaster. It is also theorized that small businesses and people working in the informal sectors suffer from declines in their incomes (Yamamura, 2015). Another vulnerability factor relates to disaster prevention. Poor people might systematically reside in areas with lower security standards such as old and unmaintained levees or structurally poor quality housing that have a higher probability to collapse during a disaster (Zoraster, 2010).[9]

On the contrary, the *risk argument* anticipates decreasing income inequality between the rich and the poor. Top income earners and the more affluent classes are likely to possess assets of higher economic value, and thus are more prone to bear the highest absolute economic damage (Masozera et al., 2007). Additionally, the source of income could influence the individual's risk level when exposed to natural disasters. The rich generate income from businesses and capital which could be more volatile in periods of natural disasters, whereas the low-and middle classes primarily rely on risk-free salaries and financial substitutions by unemployment insurances in case of unemployment (Pleninger, 2020).[10] Given this ambiguity, we first introduce a brief literature review of empirical results before formulating our hypothesis of interest.

Empirical studies put their focus on investigating the effects of natural disasters either on economic growth (see Skidmore and Toya, 2002; Loayza et al., 2012; Felbermayr and Gröschl, 2014; Hallegatte, 2015), or on income development (see Deryugina, 2017), instead of analyzing the resulting and changing patterns of income distributions. Thus, empirical evidence for causal effects on the income distribution running from natural disasters has been left fairly uncharted. Only a few studies have attempted to deal with the relationship of interest. Using a cross-country panel data design, Yamamura (2015) finds evidence for short-run increases in income inequality, but the effect disappears in the long-run. However, the study is limited to the extent that it only exploits five-year averages, losing much of the data's annual variation. Other studies exploiting panel data are restricted to data from the United States. At the state-level, findings from Miljkovic and Miljkovic (2014) suggest inequality-increasing effects of hurricanes, concluding that income inequality measured by the Gini coefficient grows by 5.4% for every 100bn US Dollar of economic damages caused by hurricanes. At the county-level, Pleninger (2020) reports decreasing effects on incomes, where the middle incomes are most adversely affected by natural disasters. When measuring income inequality for households by the Palma ratio, her results also indicate a widening gap between the shares of top incomes and the shares of incomes at the lower end of the distribution (Pleninger, 2020). Furthermore, by relying on US county-level data, Howell and Elliott (2019) show a positive and dynamic link between wealth inequality and natural disasters. Interestingly, they find evidence that aid provided by the Federal Emergency Management Agency appears to exacerbate wealth inequality, probably as it is systematically designed to restore property rather than communities.

Other case studies concentrate on regional effects of hurricanes on income inequality in the United States. In their respective research work, Masozera et al. (2007) and Logan (2006) both examine whether neighborhoods in New Orleans were impacted differently by

[9]Although the flooding levels were not different between low- and high-income communities in New Orleans(Masozera et al., 2007), the population in more severely damaged areas lived disproportionately below the poverty line (20.9% vs. 15.3%), showed higher unemployment rates 7.6% vs. 6.0%), was nearly half black (45.8% vs. 26.4%), and primarily lived in rental housing (45.7% vs. 30.9%) compared to areas that experienced only limited damage (Logan, 2006).

[10]In this context, the terms "*vulnerability argument*" and "*risk argument*" were first used by Pleninger (2020).

Hurricane Katrina based on pre-existing socio-economic conditions. They infer that the storm's impact was disproportionately borne by the poor, the unemployed, the people who rented their homes, and by the African American population, hence confirming significant inequalities in the ability of different income groups to respond and recover from the storm and flood. By applying several density functions for modeling income inequality before and after Hurricane Katrina, Shaughnessy et al. (2010) show inequality-decreasing effects. Their best fitted model based on a log-logistic distribution indicates decreasing levels of the Gini coefficient in New Orleans from 0.5881 before Katerina to 0.5776 after Katerina, and 0.5604 in 2007. Their data also reveals migration of the lowest income groups from the affected area which was likely to have an impact on changes in the income distribution.

Although all these empirical findings, with the exception of Shaughnessy et al. (2010), support the *vulnerability argument*, evidence from studies examining the effects of natural disasters on income inequality in Asian developing countries is less conclusive. For instance, Keerthiratne and Tol (2018) exploit six survey periods of district-level panel data in Sri Lanka and find inequality-decreasing effects where the richer quintiles of the income distribution disproportionately bear the highest natural disaster damages. Case studies investigating the impact of Cyclone Aila in Sundarbans region in Bangladesh in 2009 (Abdullah et al., 2016) and of the Sichuan earthquake in China in 2008 (Feng et al., 2016) present either inequality-decreasing effects or no effects on income inequality. In the aftermaths of both events, household incomes were spread more equitably across the different income groups. Bui et al. (2014) analyse the Vietnam Household Living Standard Survey from 2008 and find inequality-increasing effects on Vietnamese households induced by natural disasters.

3.2 Hypotheses development

Most of the previous empirical studies tend to corroborate the *vulnerability argument*. This is especially the case for studies related to natural disasters in the United States. Effects of Hurricane Katrina might lead to the consequence that the low-and middle-income groups would bear higher income losses than the top income earners which in turn would cause greater income inequality. Therefore, we hypothesize and test that:

Hypothesis 1 (H1): *Hurricane Katrina has a positive impact on top income shares.*

The literature of inequality economics highlights differences across the heterogeneous income share groups at the very top (see Atkinson and Piketty, 2007; Roine et al., 2009). The source of such heterogeneity are differences in income types, with capital income mainly being generated by higher income groups. It is argued that the capital share of total income is continuously decreasing with income (Pleninger, 2020). In addition to the higher volatility of capital income, the rich might also loose income deriving capital assets. Consequently, the effects of natural disasters might even vary between different top income share groups. Therefore, we would expect that:

Hypothesis 2 (H2): *The impact of Hurricane Katrina is different across top income share levels.*

In the United States, the income gap between top income groups and the bottom 90% as well as within the group of top income earners has dramatically widened. It could be argued that income groups ranked higher in the distribution pyramid would be more resilient to storms or even benefit during the phase of economic recovery. To test whether the effects of natural disasters on income inequality are pro-rich, we apply several dispersion ratios and formulate our third hypothesis as:

Hypothesis 3 (H3): *The impact of Hurricane Katrina is pro-rich and increases the income gap within the top decile.*

4 Data and inequality measures

In our analysis, we exploit annual state-level panel data for the period between 1960 and 2015. The event year is consistent with the time of landfall made by Hurricane Katrina in 2005, giving us 45 years of preintervention data. Louisiana presents the treatment state, whereas all unaffected states form the donor pool needed to create control unit. Operational definitions and original data sources are provided in Table A.1.

4.1 Outcome variables

Our outcome variables of primary interest relate to a rich set of alternative income inequality measures. The high complexity of measuring income distributions (Deaton, 2013) and the absence of a superior inequality measure requires us to account for the different ways to look at income inequality. One way to understand inequality is to examine the income distribution at different income group levels. Given an unequal income distribution, top decile income groups show disproportionately higher income shares compared to their population share, while bottom decile income groups exhibit disproportionately lower income shares. For an advanced analysis of the income distribution, Jenkins (2009) proposes to incorporate several indices that focus on changes in different income ranges. Top income shares are able to specifically measure the income dynamics of the more affluent income groups. Leigh (2007) finds empirical evidence that top income shares are strongly related to other measures of income inequality such as the Gini coefficient and advocates their utilization especially when other inequality measures are not available or are of low quality. Thus, in the first instance, our outcome variable is defined as the pre-tax national income share held by the top 1% of the income distribution. We also apply other income share measures within the top decile, like the ones at the top 0.1% level or the next 9% level, as the literature of inequality economics highlights differences across the heterogeneous income share groups, especially at the distribution's top. (see Atkinson and Piketty, 2007; Roine et al., 2009).[11] Data related to top income shares is taken from the World Inequality Database (WID) and refers to pre-tax and pre-transfer income. The WID provides a systematic framework to derive income share data from administrative tax sources, thus ensuring comparability over time and space.

To obtain a comprehensive picture of the distributive consequences of Hurricane Katrina at the very top, we use dispersion ratios that express the income share of the rich as a multiple of other shares. For example, the "top 1% to next 9%" dispersion ratio (P99/(P90-P99)) is able to measure the distribution of income directly within the top

[11]The source of such heterogeneity are differences in income types, with capital income mainly being generated by higher income groups (Pleninger, 2020). In addition to the higher volatility of capital income, the rich might also loose income deriving capital assets in the aftermath of Hurricane Katrina. Consequently, the effects of natural disasters might vary between different top income share groups.

decile of income earners. This allows us to examine which particular income group may be most affected by relating different income groups with one another. Relating different income groups with one another allows the examination of potential shifts between them. A corresponding increase would signify a pro-rich development, for example from the next 9% to the top 1% income earners. The dispersion ratios deployed in this analysis are based on our own calculations and are built on the income shares sourced from the WID data series. We are convinced that utilizing top income shares and dispersion ratios qualifies to extend the current understanding of how Hurricane Katrina might have shaped the income distribution at its top.

As a complement to these examinations of inequality, the Gini coefficient presents a single convenient measure to summarize the entire income distribution. Although it meets the desirable axioms for a proper inequality measure (Haughton and Khandker, 2009), it has its own noteworthy issues. The Gini coefficient is more sensitive to changes located in the middle of the income distribution (Frémeaux and Piketty, 2014). Additionally, several income distributions very different from each other can present the same Gini coefficient because the Lorenz curve can assume various shapes even when the size of the measured area is identical (Afonso et al., 2015). Based on this argument, Hesse (2016) goes a step further and offensively expresses surprise at the dominant use of the Gini coefficient in statistical analysis. Conclusively, the Gini coefficient is appropriate to quantify general inequality levels but possesses limited analytical value to explain changes at different points within the income distribution. Awareness of this relevant limitation has made us recognize that most of the previous studies which either strongly or even exclusively focus on using the Gini coefficient as preferred income inequality measure leave many aspects of the income distribution dynamics widely untapped. As we aim to provide a complete picture on the impact of Hurricane Katrina on the income distribution at the very top but also on measures of inequality levels that examine combined effects from the top and the bottom, we analyse data for the Gini coefficient coming from Mark W. Frank. In his work, Frank (2014) constructs and constantly updates a set of annual state-level income inequality measures derived from individual tax data sources.[12]

Other alternative measures obtained from Frank (2014) and applied in the robustness analysis include the Atkinson index, the relative mean deviation and Theil's entropy index.[13] While all are constructed in a way to assess inequality over the entirety of the income distribution, each of these three presents a different class of inequality measures with differences in terms of decomposability and transfer principles (Frank, 2014). For calculating the relative mean deviation, the population divides into one group that receives less than or equal to mean income and another one with incomes above the mean. It can be defined as the percentage of total income that should be transferred from the richer income group to the other group with incomes below the mean; so, that both groups have an identical mean income (Kakwani, 1980). Technically, this measure varies in a range from zero to two, with larger values signifying higher income inequality (Frank, 2014). The Atkinson index is based on a social welfare function and incorporates some social justice into the measurement of income inequality. It aims to compute the proportion of total income that would be required to attain an equal level of social welfare as at present if incomes were perfectly distributed (De Maio, 2007). The measure is

[12] Our data was last updated in January 2021. To download the pertinent data set provided by M.W. Frank please access: `www.shsu.edu/~eco_mwf/inequality.html`.

[13] For a detailed and technical explanation of the alternative measures please see Frank (2014), Haughton and Khandker (2009) and Kakwani (1980).

bound between zero and one, where zero indicates no need for reallocation of incomes to achieve an equal level of social welfare. A higher value, for example 0.3, implies that an equal level of social welfare can be realized with merely 70% of the current total income (1–0.3 = 70%), indicating that 30% of income would not even have to be generated if income were just equally distributed. In other words, if a richer individual renounces parts of its income to achieve a more equal income distribution, less income is required to realize the same social welfare level. However, this depends on an individual's willingness to accept a lower income level in exchange for a more equally distributed income distribution. Indeed, the Atkinson index depends on the degree of a population's aversion to inequality, a theoretical sensitivity parameter chosen by the researcher to weight incomes (Afonso et al., 2015). By varying the value of the inequality aversion parameter which ranges from zero to infinity, the Atkinson index becomes sensitive to incomes at different parts of its distribution. The one employed by Frank (2014) equals 0.5, a value more sensitive to changes at the top of the income distribution. Finally, the Theil's entropy index compares the income and population distribution structures, analysing discrepancies between the distribution of income and the distribution of population between defined income groups (Conceição and Ferreira, 2000). If all income groups have an income share equal to their population share, the overall Theil's entropy index is zero (Conceição and Ferreira, 2000). This presents a state of equal income distribution. Larger relative distances translate into higher levels of income inequality. The Theil's entropy index as the advantageous characteristic to be decomposable and to satisfy the transfer principles, as well as the feature to assign a weight to distances between incomes in different parts of the income distribution (Frank, 2014; Afonso et al., 2015).

4.2 Predictor variables

To achieve a good preintervention matching of the Synthetic Control Group over an extended period of time, it is essential to use an appropriate set of predictor variables. Among the most important drivers of income inequality at the country-level suggested by the literature are economic factors such as: economic growth and openness; technological progress; financial development; and the presence of systematic banking crises; as well as political factors like decreases in strength of trade unions, top marginal tax rates, and government spending (see Atkinson and Piketty, 2007; Roine et al., 2009; Scheve and Stasavage, 2009; Neal, 2013; Dorn and Schinke, 2018; Huber et al., 2019). Our selected predictors are in accordance with the previous literature on inequality. First, economic development is defined as the logarithm of personal income per capita in nominal terms, and as such it controls for any distributional effect due to different income levels. The personal income consists of wages, proprietor's income, dividends, interest, rents, and government benefits. As such it also controls for any distributional effect due to social security transfers. Data is retrieved from the Bureau of Economic Analysis (BEA).[14] To account for changes in population demographics and shifts in labor market resources, we include the total population and total employment numbers by state. Data for both measures are also sourced from the BEA. The main variables to capture effects of education on income inequality are taken from Frank (2009) who developed two human capital attainment-to-population ratios, one related to high school attainment and the other linked to college attainment. These can be interpreted as the percentage of total population that holds at least a high school diploma, or a baccalaureate or first professional

[14] Available at https://www.bea.gov/data/economic-accounts/regional

degree, respectively.

Due to a lack of direct measures related to state-level taxation laws, labor market regulation, and the size of government activity, we deploy three subindices of the Economic Freedom Index provided by the Fraser Institute in order to capture those effects on income inequality.[15] Each subindex ranges between 0 and 10, with the highest score indicating the highest degree of economic freedom (Stansel et al., 2020). For example, the subindex related to the size of government activity is lower for states described by growing levels of government consumption expenditures, greater levels of transfers and subsidies, higher number of mandatory government programs to pay for retirement and disability insurances (Stansel et al., 2020). Second, higher tax burdens on incomes and properties translate into lower scores of taxation subindex (Stansel et al., 2020). Third, lower scores of the subindex related to labor market regulations are a result of higher minimum wages that restrict the ability to freely negotiate contracts, more restrictive hiring and firing regulations, and stronger centralized collective bargaining power (Stansel et al., 2020). Admittedly, each subindex is evaluated through the lens of how supportive or destructive it is for economic freedom, but given the underlying objective scale of judgment, we firmly believe that these measures provide indirect indications on potentially important developments related to income inequality. Thus, we prefer to include these indirect measures rather than to refrain from exploiting available data for our prediction of the Synthetic Control Group.

5 Methodology

5.1 Methodology

The empirical objective of this paper is to estimate the treatment effect of Hurricane Katrina on different inequality measurements in order to test our hypotheses developed in section 3. In applied economics, the most reliable impact evaluation strategy to estimate a treatment effect is randomized control trials (RCT), where the researcher can experimentally assign units of observation to treatment and control groups. In empirical exercises exploring issues with natural disasters applying RCT is obviously impossible. However, we can exploit the fact that the majority of the destruction of Hurricane Katrina occurred mostly in the state of Louisiana. Given this, we treat Hurricane Katrina as a natural experiment to explore the relationship between natural disasters and inequality. Since we use annual state-level panel data where only a handful of states were "treated" (i.e. affected by the natural disaster), the most appropriate methodology to estimate the causal effect of the Hurricane Katrina on inequality is the synthetic control method for comparative case studies developed by Abadie and Gardeazabal (2003) and later expanded in Abadie et al. (2010).

We use the synthetic control method to estimate the treatment effect of Hurricane Katrina on top income shares and other commonly used inequality measurements in the state of Louisiana. This method uses a weighted combination of untreated units, called donors, to create, in our case, a synthetic Louisiana that works as a counterfactual of what would have happened to Louisiana if Hurricane Katrina would not have occurred. Differences in our outcome of interest between the observed and synthetic Louisiana after the disaster can be attributed to Hurricane Katrina. In order to construct synthetic

[15] Data is available at www.fraserinstitute.org/studies/economic-freedom, access July 2021.

Louisiana, we use all states in the United States with available data in the World Income Inequality database that were not directly affected by the hurricane.[16]

The most crucial concerns when implementing a synthetic control method are the following: the length of the pre-treatment period, the choice of donor states, the use of appropriate predictor variables, and the assignment of weights across states. First, in synthetic control method a long pre-treatment period is necessary to create a valid counterfactual since the credibility of the method depends on how well, in our case, synthetic Louisiana tracks actual Louisiana. We include data from 1960, that is 45 years before Hurricane Katrina, allowing us to have a convincing fit before the disaster. Second, the synthetic control method requires that the pool of donor units include states with similar socioeconomic characteristics as the treated unit. In our case, the donor states used in the analysis include all states in the US where data is available. Note that we exclude states that were affected by Hurricane Katrina since including them could bias the true effect of the disaster on inequality. Third, to properly construct a synthetic control method, we need to include predictor variables that affect inequality both before and after the treatment. To construct synthetic Louisiana, we use variables that are in accordance with previous studies on inequality. Furthermore, we include inequality indicators from 1961 to 2001 in five years intervals as predictors.[17] Finally, based on those states and predictors, we select weights that minimize the difference between the pre-Katrina inequality between actual and synthetic Louisiana. The weights on each state in the donor pool are non-negative and together they sum to one. In our empirical exercise, many states are assigned a weight very close to zero, with only a small number of states receiving non-zero weight for each outcome variable.

The synthetic control method is a novel methodology for quantitative case studies as it let us estimate treatment effects for situations where a single unit is treated. As argued by Rubolino and Waldenström (2020), the synthetic control method has some advantages over regression models such as difference in differences and fixed effect regressions. First, it relies on an algorithm to create the control unit, so researchers cannot deliberately choose the control region. Secondly, this method is transparent given that it allows to keep track of the exact weight of each donor unit used and the precise weight that each predictor variable has in the analysis. Finally, the synthetic control method allows the effects of unobserved variables on the outcome to vary over time (Abadie et al., 2010).

Migration may pose a threat to our identification strategy if the decision or possibility to migrate differs by economic conditions. We can illustrate this with two extreme examples. First, massive net out-migration of only the poorest income earners would lead to an increase in the average income of the bottom of the 90% of the income distribution. This could very well translate into a decrease of the top income shares given that the average income of the society would increase. Second, large out-migration of the top income earners would lead to a decrease in the average income of the whole society. This type of selective migration of the richest members of society would change the composition of the top income earners as individuals who previously were not part of the top of the income distribution will become part of it. As in the first example, this compositional change may result in a decrease on the top income shares given that richest individuals are excluded

[16] We exclude Alabama, Florida, and Mississippi because they were partially affected by Hurricane Katrina. Indiana and Montana are not included since WID does not provide precise information on top income shares for them. Finally, we don't include Washington, D.C. since it's not considered a state.

[17] As robustness checks, we consider different years and inequality averages as predictors. The results are mostly identical.

from the income distribution. These examples are extreme cases of selection and unlikely to occur, but they indicate that our synthetic control results would underestimate the true effect of Hurricane Katrina on top income shares if the disaster disproportionately affects the out-migration decision of either the richest or the poorest members of society. In the aftermath of Hurricane Katrina, there were huge mobilizations outside of the city of New Orleans towards non-devastated regions. Internal reallocations within the state of Louisiana together with out-migration towards eastern parts of the state of Texas were common coping strategies for affected individuals. According to the 2006 American Community Survey organized by the U.S. Census Bureau, an estimated 118,552 individuals who resided in Louisiana in 2005 migrated to Texas by 2006. Lower-income households were more likely to out-migrate from Louisiana to counties like Harris and Dallas in the state of Texas than their wealthier counterparts (Fussell, 2015). This suggests that the estimated effect of Hurricane Katrina on inequality, in the short-run, is likely to be underestimated. It's more difficult to understand the sign of the possible migration-induced bias in the mid- and long-run after Hurricane Katrina because in-migration to Louisiana could be a combination of returnees and outsiders attracted by the revitalized economy.

5.2 Inference

We also provide information about the statistical significance of the estimated treatment effects. Following Cavallo et al. (2013), we use permutation tests for each year after the natural disaster. To obtain p-values, we first reassign the treatment to all control units in the donor pool that were originally not exposed to the storm. Then, we iteratively apply the synthetic control method as if they were affected by Hurricane Katrina. Each time the actually affected state of Louisiana is shifted into the donor pool, replacing the respective control unit. After implementing the simulated placebos, we obtain each year's treatment effect for each placebo analysis. Intuitively, we would expect the respective placebo effect to be close to zero. This is due to the simple fact that there was no treatment from which an effect could have occurred. Finally, we rank the actual year-specific effect of Hurricane Katrina on Louisiana's outcome of interest in the distribution of the values of the year-specific placebo effects. The p-values are the proportion of placebo effects with a larger estimated effect than the observed effect of Hurricane Katrina on actual Louisiana's inequality for each period after the natural disaster. If the distribution of placebo tests performed generate many placebo effects of similar or larger magnitude as the one found for actual Louisiana, then our results would rather be observed by chance instead of exhibiting robust evidence for an impact on Hurricane Katrina on income inequality (Galiani and Quistorff, 2017).

Units with high pre-treatment root mean squared prediction error (RMSPE) may be more volatile in any posttreatment year than units with low RMSPE due to poor fit (Absher et al., 2020). We deal with this concern in two ways. First, as in Absher et al. (2020), we divide each effect (both placebos and real) by the pre-treatment root mean squared prediction error; therefore, we report standardized p-values. Secondly, to obtain the p-values, we do not include states where the RMSPE is 2.0 greater than Louisiana's RMSPE in the pre-treatment period.

6 Results

This section serves to first transparently summarize the outputs concerning the construction of synthetic Louisiana. This involves displaying the weights assigned to each predictor variable as well as to states in the donor pool. Then, we present our main results obtained by applying the Synthetic Control Method. The four defined baseline inequality measures include the top 0.1% and top 1% income shares, the next 9%, and the dispersion ratio between the top 1% and the next 9%. This section completes with the performance of robustness tests.

6.1 Baseline results

6.1.1 Construction of Synthetic Louisiana

The creation of a control unit that best resembles the pre-treatment characteristics of actual Louisiana is essential for the validity of our analysis. Indeed, the synthetic Louisiana for each inequality measure was constructed as a weighted average of some states chosen from the donor pool and was based on selected predictor weights. To ensure a high degree of transparency in the composition of the respective synthetic Louisiana, we provide the pertinent information in the following tables.

Table 1: Donor pool states and share to construct synthetic Louisiana

State	Weight			
	Top 0.1%	Top 1%	Next9%	T1/N9 ratio
Kentucky	0.024	0	0.169	0.211
New Mexico	0	0	0	0.078
Ohio	0	0	0.123	0
Tennessee	0.227	0.312	0.303	0.172
Texas	0.252	0.234	0.074	0.248
West Virginia	0.496	0.454	0.330	0.291

Note: Only donor states with non-trivial weight are shown.
Table A5 shows all the donor states and their weight.

Table 1 shows the weights of control states used to compose the synthetic control. Across all four baseline inequality measures, West Virginia is the most heavily weighted, with weights ranging from 29.1% to 49.6%. Another commonality is the selection of Tennessee and Texas as relevant donor states, albeit showing varying weights. The top 1% income share only consists of three donor states, while the other baseline inequality measures are based on four to five donor states. It appears that none of the synthetic controls is disproportionally driven by only a single donor state.

Table 2: Synthetic Louisiana predictor weights

Variables	Top 0.1% Synthetic	Top 1% Synthetic	Next 9% Synthetic	T1/N9 ratio Synthetic
Top 0.1% Income Share	0.1272			
Top 1% Income Share		0.0232		
Next 9% Income Share			0.0562	
T1/N9 Ratio				0.0000
Log Income per capita	0.2497	0.0082	0.0290	0.0002
Log Population	0.1250	0.2218	0.0310	0.9971
Log Employment	0.1168	0.6766	0.8567	0.0018
ECF Taxation	0.0131	0.0087	0.0027	0.0000
ECF Government Spending	0.0181	0.0240	0.0068	0.0000
ECF Labor Market Regulations	0.2043	0.0041	0.0121	0.0000
High School Attainment	0.0494	0.0222	0.0000	0.0000
College Attainment	0.0964	0.0113	0.0055	0.0008

Note: This table shows the predictor weights to create synthetic Louisiana

In addition to this, examining the predictor weights sheds further light into the composition of the synthetic controls. Table 2 lists the weights given to each predictor based on the standard method that includes all states as donor states. Lagged outcome variables are often referred to as an important predictor but also have the potential to absorb too much prediction power from other predictors. In our analysis, none of the four baseline inequality measures gives too much weight to their respective lags, allowing other predictors to receive adequate weights as well. The income share of the top 0.1% is the most balanced, with the heaviest weight of around 25% is assigned to the logarithmized income per capita. This contrasts the strong weights given to the logarithmized employment in case of the top 1% and the next 9% income shares. The prediction of the dispersion ratio seems to solely concentrate on logarithmized population. Nevertheless, we are convinced that the heavy weight assigned to logarithmized population in case of the dispersion ratio is not a drawback of our analysis. As can be seen in the next subsections, this confidence is based on congruent results obtained for the top 0.1% and top 1% income shares and the dispersion ratio, even though each inequality measure possesses different predictor weights.

Table 3: Inequality predictor means: Baseline inequality measurements

Variables	Louisiana	Top 0.1% Synthetic	Top 1% Synthetic	Next 9% Synthetic	T1/N9 ratio Synthetic
Top 0.1% Income Share	0.0439	0.0431			
Top 1% Income Share	0.1237		0.1203		
Next 9% Income Share	0.2624			0.2625	
T1/N9 Ratio	0.4701				0.4518
Log Income per capita	8.9935	8.9968	9.0089	9.0076	9.0153
Log Population	1.3966	1.3541	1.3793	1.368	1.3963
Log Employment	0.6713	0.6353	0.6737	0.6670	0.7071
ECF Taxation	6.5371	5.8367	5.9998	5.8795	5.9748
ECF Government Spending	6.4551	6.7819	6.9902	6.7227	7.0789
ECF Labor Market Regulations	3.3642	3.4125	3.5249	3.5095	3.6375
High School Attainment	0.4122	0.4263	0.4271	0.4307	0.4258
College Attainment	0.0863	0.0821	0.0827	0.0823	0.0857
RMSPE	-	0.0035	0.0059	0.0053	0.0210

Note: This table shows the indicator variables and the average pre-Katrina inequality for observed and synthetic Louisiana.

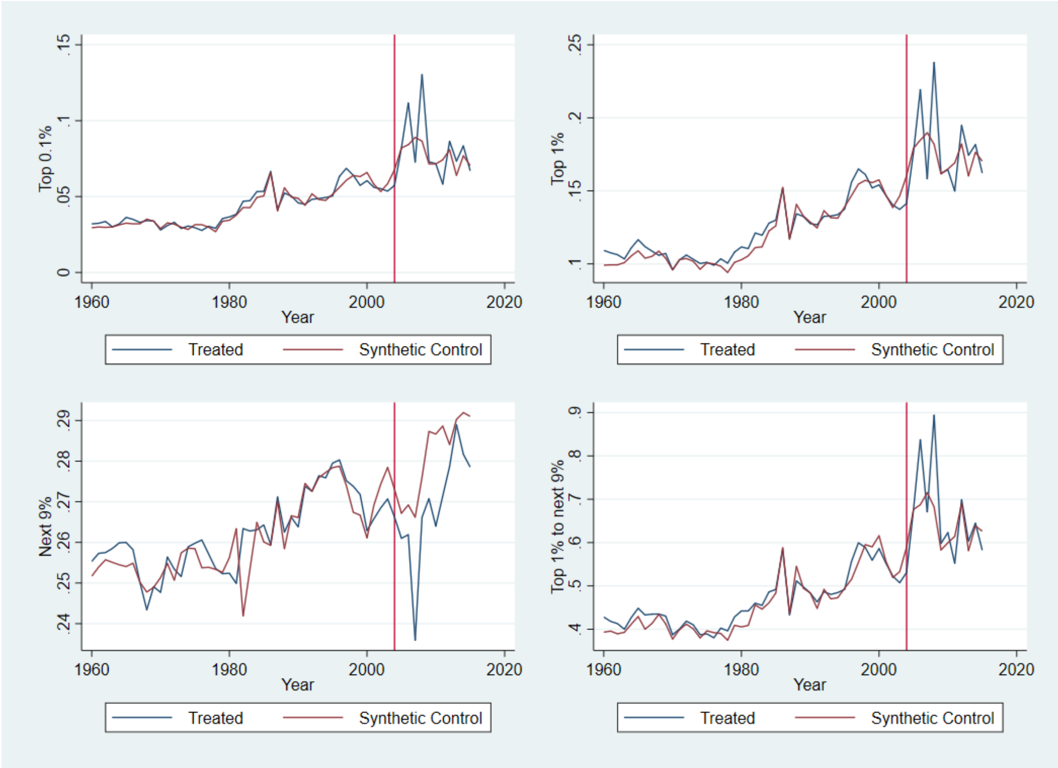
Finally, we report the values of the predictor variables used in the baseline model to find the optimal synthetic controls during the pre-treatment period. One of the key outcomes of the Synthetic Control Method is the estimate of the root mean square predicted error (RMSPE) between the actual and synthetic Louisiana, measured in the pre-treatment period. In table 3, the RMSPE is documented to show that the synthetic controls are chosen to best fit the trajectories of the control variables and the respective inequality measure. For all of them, the RMSPEs exhibit low levels ranging between 0.0035 and 0.0210, which translate into very close matches between actual and synthetic Louisiana.

6.1.2 Comparison between Actual and Synthetic Louisiana

The causal effect of Hurricane Katrina on income inequality at the top of the distribution is measured as the difference between the post-treatment trajectory of the respective top income share for the treatment state of Louisiana and its synthetic control. The goodness of fit of synthetic Louisiana is then assessed by calculating its deviation from the actual Louisiana during the pre-treatment period. Figure 1 shows the trajectories of the four defined baseline inequality measures for each actual and synthetic Louisiana. The blue line represents the evolution of income inequality for actual Louisiana and the red one for synthetic Louisiana. The vertical line marks the event year.

The pre-treatment trajectories observed for the top 0.1% and top 1% income shares are well-replicated by their respective synthetic controls. This indicates that the post-treatment trajectories of synthetic Louisiana provide a reasonable approximation to trajectories that would have occurred if Hurricane Katrina would never have happened. This pattern is confirmed by the other two baseline inequality measures, although the fit of the next 9% trajectories experiences somewhat higher volatility with more fluctuating deviations. The estimated effects of Hurricane Katrina on top 0.1% and top 1% income shares mirror each other and only vary in terms of magnitude. In the year immediately following Hurricane Katrina both measures experienced strong surges based on a year-to-

Figure 1: Income inequality in Louisiana before and after Hurricane Katrina



Note: The figures show the trends for the baseline inequality measurements in Louisiana and synthetic Louisiana before and after Hurricane Katrina.

year change, with the top 0.1% income share increasing by 36.22% and the top 1% income share rising by 24.59%. Compared to the modest shifts of 2.07% and 2.96% for both top income share measures in synthetic Louisiana, the observed increase in real Louisiana was 8 to 12 times stronger. However, these effects are first inversed by sharp declines of comparable magnitude in 2007, but then again turn positive with historically stark growth rates of 79.37% observed for the top 0.1% income share, and 50.44% recorded for the top 1% income share. This highly volatile pattern seems to phase down after another sharp drop in both top income shares four years after the storm. Comparing these actual developments with the ones obtained from the synthetic Louisiana suggests that the evolution of both top income shares in the theoretical absence of Hurricane Katrina would have been tremendously less volatile, and would have reached lower levels of income inequality. Nevertheless, the differences between the actual and synthetic trajectory in the first years of post-treatment period do not indicate neither inequality-increasing nor inequality-decreasing effects. Instead, it can be inferred that Hurricane Katrina has thoroughly shaken the income distribution at its very top. This high volatility was felt more intensely by superrich income earners residing in the top 0.1% income share group. Therefore, our hypothesis that Hurricane Katrina has a positive impact on top income shares can only partially be confirmed for the first year after the storm. However, this short-term inequality-increasing effect is not persistent. Any long-term effects are negligible, essentially because the prediction of the synthetic controls once more closely matches the trajectory of actual Louisiana.

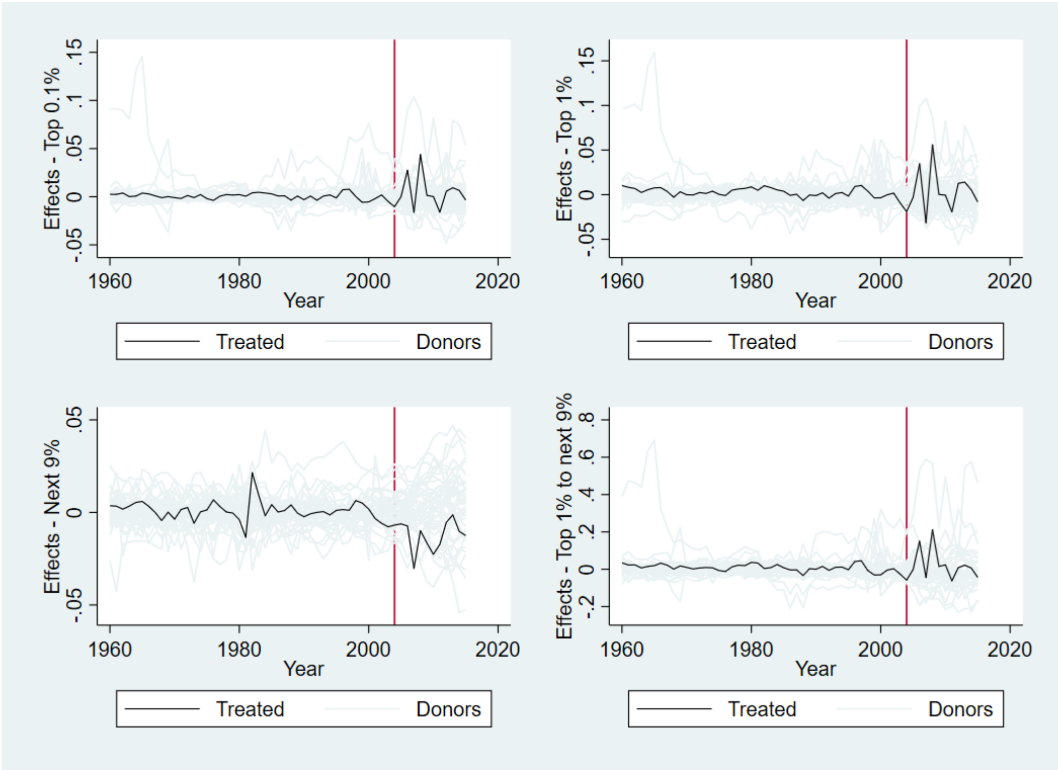
With respect to our second hypothesis, it could be seen that the impact of Hurricane

Katrina is different across top income share groups. When analyzing the group of the next 9% of income earners, our empirical findings indeed show lasting differences between the actual and synthetic trajectory for almost all years following the event year, indicating negative impacts of Hurricane Katrina only for high income earners located in the next 9% of the income distribution. This would not only support our second hypothesis but would also be in accordance with the vulnerability argument. Income earners in the lower part of the top decile are more vulnerable than top 1% income earners. To investigate the pro-rich effect of Hurricane Katrina, we included the dispersion ratio between the top 1% and the next 9% into our main analysis. An increase in this ratio signifies a widening income gap even within the more affluent income share groups located at the top of the income pyramid. Although we observe a highly volatile pattern comparable to the ones seen in the top 0.1% and top 1% income shares, we interpret our result as inequality-increasing and thus as pro-rich over the course of the first three years following the storm. We base this inference on the two large positive differences and the minor negative difference between actual and synthetic Louisiana observed in the first three years after the event. Again, long-term effects do not seem to play a role. Thus, we see our third hypothesis as partially confirmed for the short run.

6.1.3 Analysis of Statistical Significance

After having calculated the treatment effect, we assess statistical significance of our main results by running "in-space" placebo tests. One way to determine the validity of the placebo tests is the eyeball test. Figure 2 portraits the results of the placebo tests obtained for our set of main income inequality measures. The black line denotes the gap estimated for Louisiana, which is the difference between actual Louisiana and its synthetic control. Each of the grey lines marks the gap associated with each of the placebo tests performed, showing the difference between each state in the donor pool and its respective synthetic control. Again, the red line presents the treatment year.

Figure 2: Placebo tests



Note: Each figure shows a series of placebo tests for different inequality measures. The bold line is the difference between the observed Louisiana and the synthetic control and the gray lines represent the placebo tests using the donor countries.

As the figure makes apparent for the cases of the top 0.1% and the top 1% income share variables, the difference between actual Louisiana and its synthetic control is larger than the same difference for most of the placebo states in the very first year of post-treatment period, and continues to be seemingly more volatile in the following three years. We interpret this pattern as first suggestive indication of causal effects of Hurricane Katrina on income inequality at the very top of the distribution. The inference for the dispersion ratio resembles this conclusion. For the income group of the next 9%, the placebo tests confirm a negative impact of Hurricane Katrina due to the larger negative estimated post-treatment gap of Louisiana compared to the same gaps observed for the majority of the donor states. In the long run, however, the black lines of all four income inequality measures appear to revert to the centre of the distribution of estimated gaps, indicating that there is no treatment effect of Hurricane Katrina on income inequality five years after the storm. Nevertheless, the analysis of appearance can only be interpreted as suggestive.

To quantitatively evaluate statistical significance, it has to be examined whether the estimated treatment effect of actual Louisiana is large relative to the distribution of the simulated treatment effects estimated for the states not exposed to the storm. From this inferential exercise, a p-value can be constructed. According to Galiani and Quistorff (2017), that p-value can be interpreted as the proportion of control units that have a simulated treatment effect at least as large as the treatment effect obtained in actual Louisiana. For each year in the post-treatment period, Table 4 reports the treatment effect and the corresponding p-values. We also report standardized p-values, which partially capture the possibility that poorly fit donor states may be highly volatile in the post-treatment period as explained in Section 5.

Table 4: The effect of Katrina on top income shares

	Top 0.1% income share			Top 1% income share		
Year	Effect	p-value	std p-value	Effect	p-value	std p-value
2005	-0.000	1.000	1.000	-0.003	0.789	0.789
2006	0.028	0.000	0.000	0.035	0.026	0.000
2007	-0.016	0.105	0.026	-0.032	0.000	0.000
2008	0.044	0.000	0.000	0.056	0.000	0.000
2009	0.001	0.842	0.842	0.000	1.000	1.000
2010	0.000	0.974	0.974	-0.000	1.000	1.000
2011	-0.0160	0.184	0.105	-0.019	0.237	0.211
2012	0.006	0.658	0.632	0.013	0.500	0.526
2013	0.009	0.394	0.316	0.014	0.316	0.421
2014	0.007	0.632	0.579	0.005	0.763	0.816
2015	-0.003	0.816	0.763	-0.008	0.632	0.526
	Next 9% income share			T1/N9 ratio		
Year	Effect	p-value	std p-value	Effect	p-value	std p-value
2005	-0.006	0.282	0.282	-0.002	0.947	0.921
2006	-0.007	0.308	0.205	0.150	0.000	0.000
2007	-0.030	0.000	0.000	-0.045	0.342	0.368
2008	-0.010	0.436	0.410	0.212	0.000	0.000
2009	-0.017	0.205	0.103	0.015	0.789	0.763
2010	-0.023	0.154	0.077	0.024	0.684	0.658
2011	-0.017	0.308	0.128	-0.062	0.421	0.263
2012	-0.005	0.821	0.821	0.009	0.947	0.947
2013	-0.001	0.872	0.897	0.022	0.868	0.842
2014	-0.010	0.487	0.461	0.006	0.947	0.947
2015	-0.013	0.436	0.359	-0.044	0.500	0.421

Note: This table shows the annual treatment effects, p-values, and std p-values.

We find a positive causal impact of Hurricane Katrina in the first year following the storm in three out of four income inequality measures that is statistically significant at the 1% level. This holds for both p-values reported, albeit the treatment effect observed for the top 1% income share in 2006 slightly expands to the 5% significance level. The inequality-increasing effect only varies in magnitude. Compared to a scenario without Hurricane Katrina, the respective income shares of the top 0.1% and top 1% are 2.8 and 3.5 percentage points higher. These differences reflect increased top income shares by 33.45% and 18.98%, respectively. For the dispersion ratio, we observe a similar increase by 21.81%. The extremely volatile pattern observed in both top income share measures shows statistical significance at the 1% level, and further indicates the disrupting short-term impact of Hurricane Katrina on the income distribution at its higher end. Regarding the dispersion ratio, we find statistical relevance for the sharp increases in the first and third year following the storm, thus corroborating a causal and positive impact on the widening income gap within the top decile. Although the income group of the next 9% consistently shows negative estimates, 2007 marks the only year in which we find a statistically relevant impact. Nevertheless, a combined view on statistical significance and sign of the estimates in the post-treatment period indicate, admittingly to a somewhat weaker degree, the income share loss of the next 9% of income earners. Overall, the results obtained from the performed placebo tests propose a high level of significance of the short-term effects of Hurricane Katrina on the highest top income shares and the dispersion ratio. We find that the immediate effect of this devastating storm has a dramatic inequality-increasing consequence. This finding partially confirms our first hypothesis. Though, given the statistical significance of the following volatility in year two and three after Hurricane Katrina came ashore, the inequality-increasing impact does not seem to have a lot of staying power. Weaker evidence for an inequality-increasing impact comes from the income group of the next 9%. Any long-term effects are not statistically significant and thus negligible.

6.2 Robustness checks

In this subsection, we report robustness checks to our baseline findings using alternative inequality measures. To validate our results, we also perform sensitivity tests by using alternative specifications for our predictor variables, applying an RMSPE free of any restrictions, and running the analysis without the most influential donor state that is West Virginia.

6.2.1 Alternative inequality measures

We have presented evidence of the effect of Hurricane Katrina on income inequality using four baseline inequality measures. Here, we seek to understand whether our findings remain similar when we apply alternative top income shares and dispersion ratios, as well as other inequality measures that summarize the entire income distribution. In combination, Figures 3 and 4 plot the evolution of ten different inequality measures for each pair of actual and synthetic Louisiana over the pre- and post-Katrina period. Across all inequality measures, we use exactly the same states and predictors as those mentioned in the previous subsections and, as before, in every estimation synthetic Louisiana closely tracks actual Louisiana in the pre-Katrina period. To limit the number of tables presented below, we refer to Table A.2, in the appendix, that shows the donor pool states and their respective share to construct synthetic Louisiana for each of the different inequality measures applied to substantiate robustness. For complete transparency, we present the predictor weights and average predictor means for the entire set of alternative inequality measures in Tables A.3 and A.4 respectively.

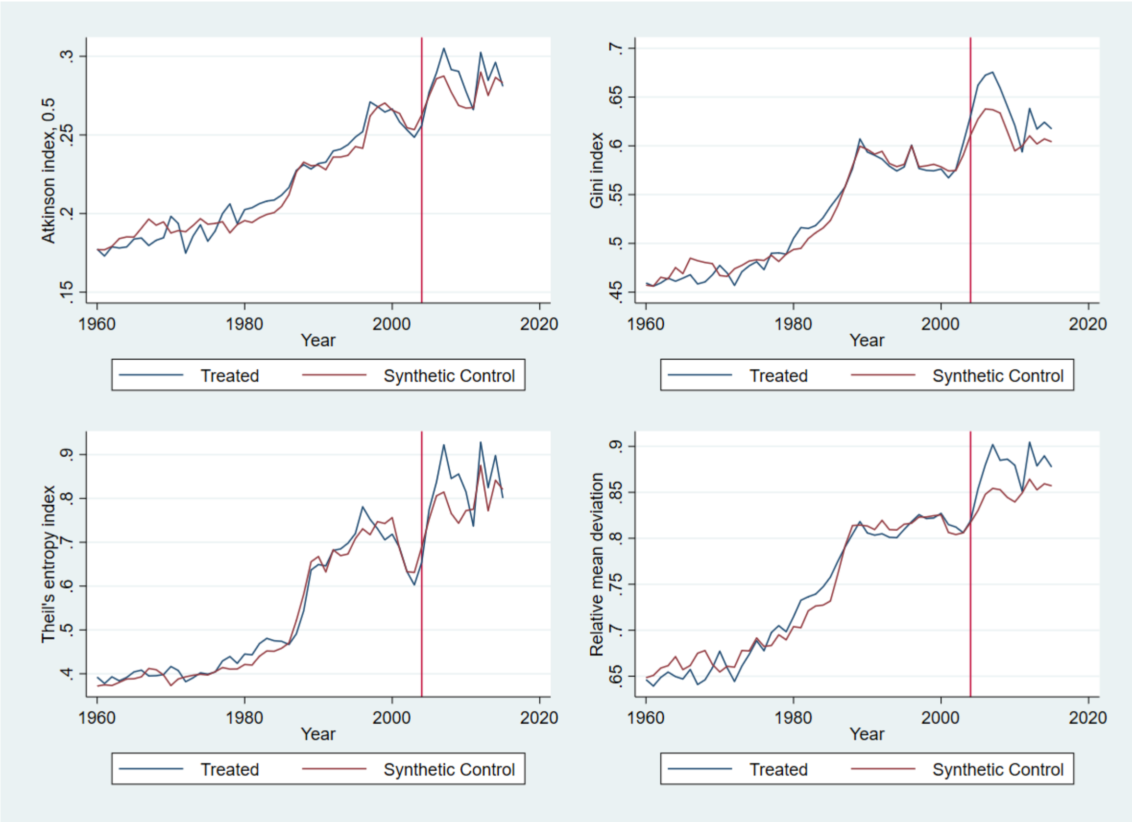
Figure 3: Income inequality in Louisiana before and after Hurricane Katrina: Alternative inequality measures I

Note: The figures show the trends for six alternative inequality measures categorized as top income shares or dispersion ratios in actual and synthetic Louisiana before and after Hurricane Katrina.

Figure 3 shows the trends using the following measures: top 5%, top 10%, next 0.9%, and next 4% income shares, and the top 0.1% to next 0.9% dispersion ratio and the top 10% to bottom 90% dispersion ratio. For the top income shares, the trends and effects are similar to the ones presented in the baseline analysis. Note that in the first year after the disaster occurred, the income share owned by the top 5%, top 10% and next 0.9% increased. However, as seen before, these income shares also become more volatile in the flowing years. The income share of the next 4% is of particular interest since it presents the top income share of those in the top 5% excluding the top 1% in the income distribution. This allows us to further disentangle heterogenous effects within the top ranked fifth percentile. It becomes clear that the estimated effect for this indicator is constantly negative for the first five years after Katrina, but the trends of actual and synthetic Louisiana seem to converge afterwards. From this, we conclude that Hurricane

Katrina had heterogenous effects on the income share groups of the top 1% and the next 4%. We also observed this heterogeneity between the top 1% and the next 9%. However, given that the results of income share of the next 0.9% mirrors the ones seen for the top 0.1% and top 1%, such heterogeneity remains unconfirmed for income share groups of higher ranks. Finally, the income share ratios presented in Figure 3 follow the same pattern shown so far; that is, the indicators increase in first year of the post-Katrina period and in the next years the indicators are very volatile. In sum, the results presented in Figure 3 corroborate our baseline findings indicating that Katrina had an inequality-increasing effect only in the short-run. See Table A.5 for the estimated treatment effects and statistical significance.

Figure 4: Income inequality in Louisiana before and after Hurricane Katrina: Alternative inequality measures II



Note: The figures show the trends for four measure of general inequality in actual and synthetic Louisiana before and after Hurricane Katrina.

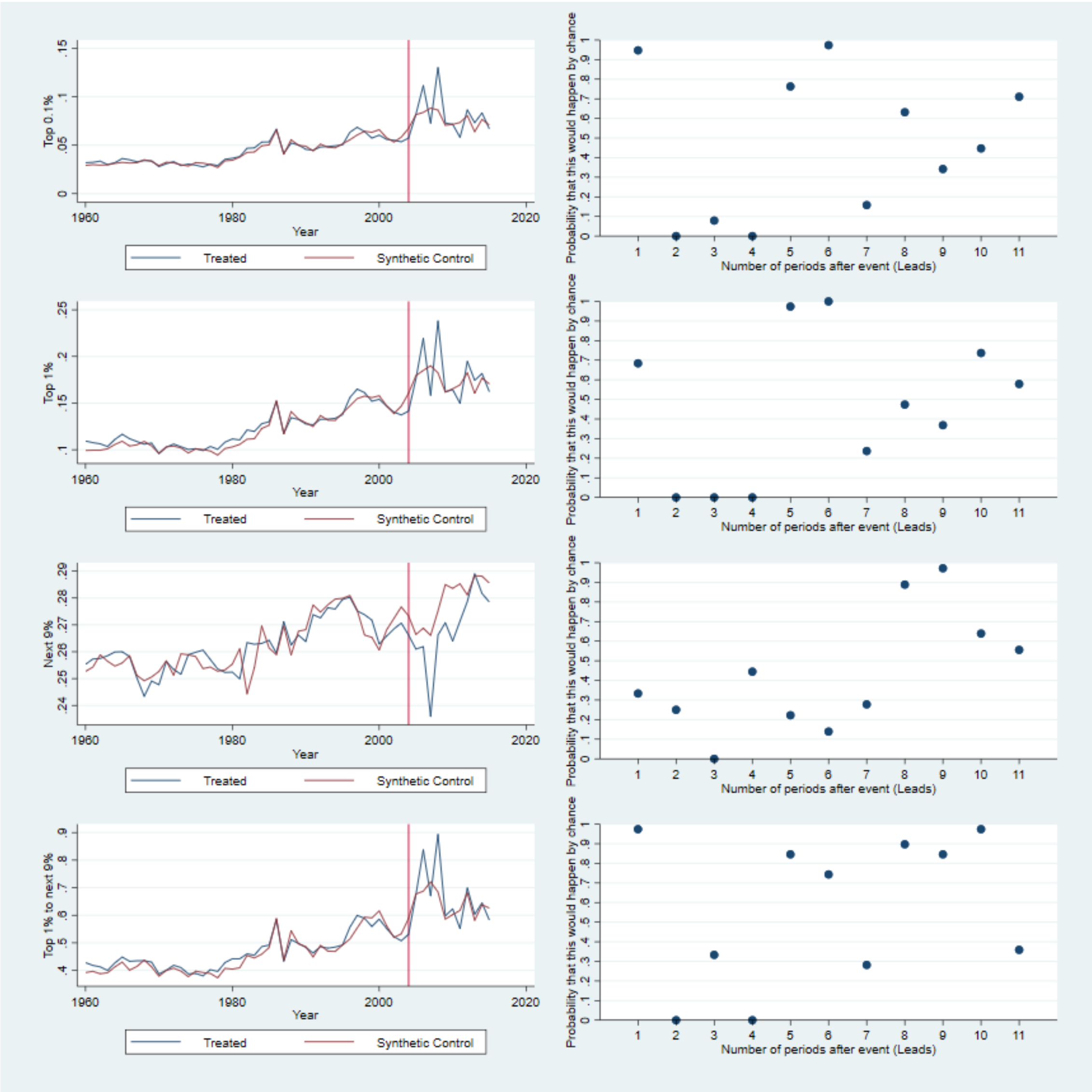
We present the trends of actual and synthetic Louisiana before and after Katrina using measures that compute more general inequality levels such as the Atkinson index, Gini coefficient, Theil's entropy index, and the relative mean deviation in Figure 4. For each of those, we observe an increase in inequality in actual Louisiana compared to the synthetic counterpart. Note that for most of these indicators, the estimated treatment effect is positive and significant in the first years; however, the estimated effects become small and statistically insignificant after the year 2010.

Given the computational and interpretative differences among the inequality measures, taking a closer analytical look at each of them further advances our understanding of various inequality dimensions. To start with, income inequality measured by the relative mean deviation would be 3.2 and 4.8 percentage points higher in actual Louisiana in the first and second year after the storm. To attain an identical mean income for everyone this means that 88.0% and 90.2% of the total income need to be transferred from the richer to the less affluent income group. This is an increase of 3.8% and 5.6% compared to synthetic Louisiana. As for the Theil's entropy index, the income inequality measured by discrepancies between income shares and population shares peaked three to five years after Katrina. Synthetic Louisiana would exhibit income inequality levels that are 9.5% to 13.1% lower than those observed in real Louisiana. Next, the Gini coefficient would expand the area located under the Lorenz curve that is intuitively associated with an increase income inequality. Here, we find income-increasing effects of economically relevant magnitude, showing that the Gini coefficients in 2006 and 2007 were 5.5% and 6.0% higher in real Louisiana. Effects of the Atkinson index seem to set in later. For the case of actual Louisiana in 2007, if income would have been equally distributed, the same level of social welfare could be attained with 69.41% of total income. For the same year, an equal level of social welfare could have been realized with 71.21% of total income in synthetic Louisiana. This means that, in case of actual Louisiana, additional 1.8% percentage points of total income could be sacrificed, and is not needed, in order to attain an equal level of social welfare.

Overall, these results confirm our previous findings of Katrina as a driver of income inequality in Louisiana in the short-run. Our results also exhibit a high degree of consistency across all the 14 inequality measures applied. We find a robust income-increasing effect in the first year after the storm for all top income share groups except the ones representing the next 4% and next 9%. Findings for other inequality measures further ascertain the positive effects of Hurricane Katrina on income inequality.

6.2.2 Sensitivity tests

Figure 5: Income inequality before and after Hurricane Katrina: Sensitivity test



Note: The top (second to top, third to top, bottom) left figure shows the trends in top 0.1% (top 1%, next 9%, top 1% to next 9% dispersion ratio) income share in actual and synthetic Louisiana using the average of top 0.1% (top 1%, next 9%, top 1% to next 9% dispersion ratio) in the pre-treatment period as a predictor. The top right figure shows standardized p-values of the effect of Katrina on top 0.1% (top 1%, next 9%, top 1% to next 9% dispersion ratio) income share.

While Figure 5 displays the trends of the top 0.1% and 1% income shares in the pre- and post-treatment periods together with their respective standardized p-values, Figure 6 equivalently shows the trends of the next 9% income shares and the top 1% to next 9% dispersion ratio. These alternative synthetic controls closely resemble the ones presented in the previous subsection. For example, the alternative synthetic Louisiana for the top 1% income share consists of 30.7% Tennessee, 23.9% Texas, and 45.5% West Virginia.[18]

[18] Alternative synthetic Louisiana for the top 0.1% of the income distribution consists of 11.2% Kentucky, 17.6% Tennessee, 26.1% Texas, and 45% West Virginia. Alternative synthetic Louisiana for the

We also observe this consistency in the composition and weighting of the donor states across the other three inequality measures. Only the dispersion ratio between the top 1% and the next 9% puts a heavy 90% weight on Kentucky.[19] However, this has no consequence to our results. The goodness of fit of these alternative synthetic controls is comparable to the results obtained from our baseline specification. The top 1% income share has an RMSPE of 0.0059 which is exactly the same as presented before. The RMSPE of the next 9% income share equals to 0.0031 and is considerably lower than the one obtained from our baseline estimation. In total, using these alternative synthetic controls leads to similar findings in terms of algebraic sign, magnitude, and significance. Results are not sensitive to the imposed specification change.

As a further sensitivity test, we drop West Virginia, the state with the highest weight in every single baseline synthetic control estimation, from the donor pool. We implement this test in order to confirm that our results are not heavily influenced by the donor selection and in particular by the highest weight that West Virginia receives when implementing the algorithm. In this case our, donor pool consists of 43 states to compose the synthetic control. Table 5 shows the respective weights for donor states excluding synthetic Louisiana. Across the four inequality measures presented in Table 5, the most important state to construct the new synthetic control is Kentucky with weights ranging from 38.4% to 90%.

Table 5: Donor pool states and share to construct synthetic Louisiana: Excluding West Virginia

State	Weight			
	Top 0.1%	Top 1%	Next9%	T1/N9 ratio
Arkansas	0	0.161	0.011	0
Kentucky	0.590	0.384	0.557	0.900
New York	0	0.001	0	0.079
New Mexico	0.093	0	0	0
Ohio	0	0	0	0
Rhode Island	0	0	0	0.021
Tennessee	0.239	0.455	0.432	0
Texas	0.078	0	0	0

Note: Only donor states with non-trivial weight are shown.

Figure 7 suggests that our results are not driven by West Virginia having a high weight since the synthetic control without the state of West Virginia still closely tracks actual Louisiana. As expected, the RMSPE of the trends presented in Figure 7 are higher than the ones presented in our baseline analysis, indicating that including West Virginia improves the fit. In terms of statistical inference, the findings do not change by excluding West Virginia from the donor pool.[20]

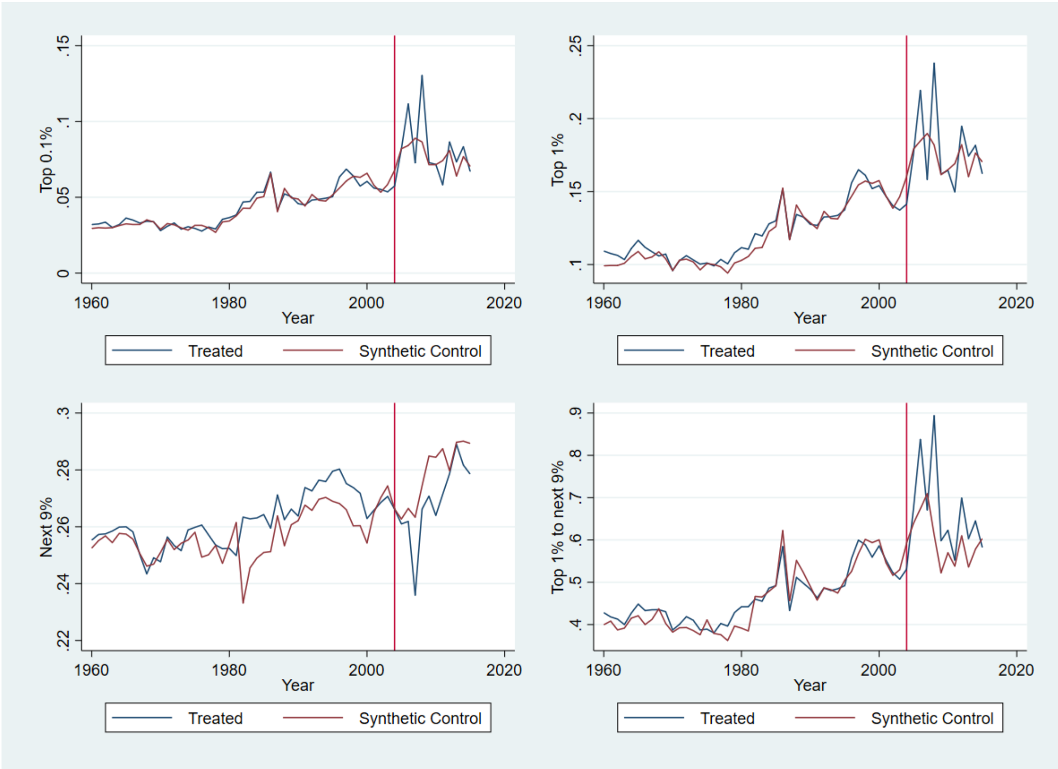
To understand whether our results are statistically significant or not, we have estimated p-values following Cavallo et al. (2013) and restricted to donor states without

next 9% income shares is constructed using 14.3% Arkansas, 5.6% New York, 48.4% Tennessee, 7.6% Texas, and 24% West Virginia.

[19] Alternative synthetic Louisiana for the dispersion ratio between the top 1% and next 9% is weighted by 90% Kentucky, 7.9% New York, and 2.1% Rhode Island.

[20] We are not reporting the RMSPE and statistical significance of the ATE that can be estimated from Figure 7. Results are available upon request.

Figure 6: The impact of Hurricane Katrina on inequality: Excluding West Virginia



Note: The figures show the trends for the baseline inequality measurements in Louisiana and synthetic Louisiana. Synthetic Louisina is constructed excluding the state of West Virginia

high root mean squared prediction error That is, states with RMSPE 2.0 times greater than Louisiana's are excluded. As explained in the methodology section, we think this is appropriate since donor states with very high RMSPE may be poorly fit and led us to over reject. With this in mind, we re-estimate our baseline analyses, but calculate the standardized p-values using all the donor states in the data. Figure A.1, in the appendix, shows the trends and standardized p-values of our baseline top income share measurements whereas Figure A.2 looks at the trends and standardized p-values of next 9% and the ratio between top 1% and next 9%. Note that the p-value in 2006, the year after Katrina, is 0.000 for the differences between observed and synthetic Louisiana for top 0.1%, top 1%, and top 1% to next 9% ratio. The difference is not statistically significant in 2006 for the next 9%. This is in line with our baseline estimations, and in general Figures A.1 and A.2 confirm that even when we include states with high RMSPE, the association between Katrina and inequality is statistically significant in the first year after the disaster.

6.2.3 Income effects

To understand the effects of Hurricane Katrina in greater detail, we explore the effects of the storm on the average income level of the top income earners (0.1%, 1%, 10%) and that of the rest of the distribution (bottom 90%). To ensure transparency, again we first provide insight into the construction of the synthetic controls, then compare the differences between actual and synthetic Louisiana, and finally perform the statistical inference.

Table 6: Donor pool states and share to construct synthetic Louisiana: Income effects

State	Weight			
	Top 0.1%	Top 1%	Top 10%	Bottom 90%
Alaska	0	0.029	0.004	0.014
Kentucky	0.196	0.163	0	0.275
New Mexico	0	0	0.067	0
Texas	0.29	0.338	0.395	0.301
West Virginia	0.514	0.471	0.534	0.409

Note: Only donor states with non-trivial weight are shown.

Table 6 reports the donor states with non-zero weight that we use to create the synthetic control. As before, West Virginia is the donor state with the highest weight across all the outcomes in Table 6. Another state with a considerable weight is Texas, with weights that range from 29% to 39.5%.

Table 7: Average income predictor means

Variables	Louisiana	Top 0.1% Synthetic	Top 1% Synthetic	Top 10% Synthetic	Bottom 90% Synthetic
Top 0.1% Average Income	1760025	1674592			
Top 1% Average Income	488137.4		469112.2		
Top 10% Average Income	150759.3			149249	
Bottom 90% Average Income	26356.9				26338.2
Log Income per capita	8.9935	9.0007	9.0334	9.0194	9.0054
Log Population	1.3966	1.3404	1.3767	1.4009	1.3952
Log Employment	0.6713	0.5986	0.6561	0.6717	0.6776
ECF Taxation	6.5371	5.5145	5.6286	5.5952	5.6403
ECF Government Spending	6.4551	6.4545	6.4596	6.4574	6.6228
ECF Labor Market Regulations	3.3642	3.2586	3.3674	3.3157	3.4205
High School Attainment	0.4122	0.4238	0.4273	0.4301	0.4233
College Attainment	0.0863	0.0815	0.0840	0.0855	0.0831
RMSPE	-	183218.9	34310.9	5999.6	755.815

Note: This table shows the predictor variables and the average pre-Katrina inequality for observed and synthetic Louisiana.

Table 7 shows the outcome and predictor means of actual Louisiana and the synthetic controls. In terms of predictor means, the synthetic controls closely resemble actual Louisiana. For example, the top 10% average income in the pre-treatment period for actual Louisiana is 150,759 US dollars, whereas the value for synthetic Louisiana is 149,249 US dollars. That is, the difference between the two Louisiana is only 1,510 US dollars which is a minor difference of about 1%.

After having created the synthetic controls, we perform an analysis on the differences. Figure 7 looks at the trends of income among the top income earners and the rest of the population before and after the hurricane. In 2006, the year after the disaster, the top 0.1% gained on average a whopping USD 2,062,889 (this is the difference between actual and synthetic Louisiana in 2006). The effect of Hurricane Katrina on average income in 2006 is estimated to be USD 275,347 for the top 1% and USD 31,969 for the top 10%. Regarding the rest of the population, the estimated impact in 2006 for the bottom 90% is

Figure 7: Average income before and after Hurricane Katrina

Note: The figures show the trends for average income in Louisiana and synthetic Louisiana before and after Hurricane Katrina.

of about USD 969. Surprisingly, the effect for the rest of the population is also positive. A possible explanation for increases in income relates to rebuilding efforts in the hurricane's aftermath. Through an interplay between diminishing labor supply and rising demand for construction workers, the construction industry experienced increases in earnings and employment (Sisk and Bankston, 2014). In their study, Corey and Deitch (2011) show that construction companies realized an average 162% increase in organizational performance in the post-Katrina period. We need to keep in mind that this group is very large and diverse. Due to data constraints, we cannot disentangle the possibility of a heterogeneous effect among the rest of the population. Figure 7 also shows Hurricane Katrina seems to create high volatility on average income for the top income earners in the middle- and long-run. Although, we see some indications of convergence in the trends in the long-run. With respect to the bottom 90%, Figure 7 reports that synthetic Louisiana is always above the observed Louisiana, suggesting a positive impact on average income.

Table 8: The effect of Katrina on average income

		Top 0.1%			Top 1%	
Year	Effect	p-value	std p-value	Effect	p-value	std p-value
2005	28722.9	0.968	0.968	-36720.9	0.576	0.576
2006	2062889	0.000	0.000	275347.2	0.000	0.000
2007	-178500.8	0.677	0.613	-52828.4	0.454	0.545
2008	3119404	0.000	0.000	405283.1	0.000	0.000
2009	538146.8	0.419	0.419	74013.3	0.575	0.606
2010	528860.4	0.452	0.452	85672.7	0.515	0.667
2011	-644670	0.516	0.452	-87061.8	0.576	0.636
2012	509345.8	0.613	0.645	83735.2	0.636	0.788
2013	563027.6	0.548	0.581	69043.6	0.545	0.757
2014	552192.5	0.548	0.581	41517.7	0.758	0.818
2015	-85156.45	0.871	0.871	-40308.3	0.727	0.788
		Top 10%			Bottom 90%	
Year	Effect	p-value	std p-value	Effect	p-value	std p-value
2005	-11702.4	0.219	0.344	415.7	0.739	0.565
2006	31968.9	0.000	0.000	969.6	0.696	0.565
2007	-8071.2	0.531	0.531	8814.8	0.000	0.000
2008	47877.3	0.000	0.031	1275.8	0.696	0.565
2009	9144.3	0.531	0.594	4409.4	0.087	0.000
2010	12385.9	0.469	0.500	6084.5	0.000	0.000
2011	-13879.2	0.437	0.531	4213.3	0.174	0.043
2012	10190.9	0.687	0.719	1560.6	0.652	0.435
2013	7473.8	0.687	0.750	691.9	0.870	0.826
2014	1820.0	0.875	0.906	2205.1	0.435	0.391
2015	-6761.9	0.719	0.750	2571.9	0.435	0.304

Note: This table shows the annual treatment effects, p-values, and std p-values.

Table 8 shows the estimated treatment effects with the respective p-values. The estimated treatment effect of Hurricane Katrina on average income for the top income earners (0.1%, 1%, and 10%) is statistically significant in 2006 and in 2008, we cannot reject the null hypothesis that the effect is zero for the other years. In both years, 2006 and 2008, the effect is positive for the top income earners and of larger magnitude, especially for the superrich (top 0.1%). The effect of the disaster on the average income of the bottom 90% is statistically significant at the 1% in 2007, 2009, and 2010.20 The effect is positive in all those years. In sum, Table 8 indicates that the superrich substantially gained after the disaster hit Louisiana and they gained at higher rates than the rest of the population. It is also interesting to see that the bottom 90% also experienced some gains, yet we do not know what group is gaining within the bottom 90%.

7 Conclusion

We examined the causal impact of Hurricane Katrina on income inequality in the United States using the Synthetic Control Method. Based on a long pre-intervention period of 45 years and various predictor variables, we estimate what would have happened to the income distribution in Louisiana, had this state not been damaged so severely by the devastating storm in 2005. The unique contribution of our study can be observed in two ways. To the best of our knowledge, we are the first to advance the understanding of the causal relationship between Hurricane Katrina and the income distribution with this quantitative and novel approach. This approach allows for constructing a synthetic Louisiana, controlling for the time-varying nature of unobserved heterogeneity. Further, to account for heterogenous income inequality effects, we employ a rich set of income inequality measures such as top income shares, dispersion ratios and more general income inequality measures such as the Gini coefficient.

Our estimates provide new evidence on the short- and long-run income inequality effects of one of the most devastating natural disasters ever hit the United States. We find that Hurricane Katrina has a short-term positive impact on top income shares for the first year after the storm. The magnitude of this income-inequality increasing impact is unprecedented within the period of observation and becomes larger for income share groups closer to the top. By applying several income inequality measures, we attempt to disentangle heterogenous effects across different income groups. The positive short-term effect in the first year after the storm is robustly confirmed across most income inequality measures applied. For the income groups of the next 4% and next 9%, we find a consistently negative, but mostly insignificant, treatment effect in the post-Katrina period. This indicates that income earners in the lower part of the top of the income distribution are more vulnerable than top 1% income earners.

The differences between the true and synthetic Louisiana in the following years are highly volatile. We observe two paradigm changes substantial in magnitude and mostly with statistical significance across top income shares and dispersion ratios. A negative one from the first to the second year followed by a positive one from the second to the third year. This finding confirms that the strong short-term inequality-increasing effect is not persistent. The mechanisms behind this result are yet to be identified, but our results show that Hurricane Katrina has thoroughly shaken the income distribution at its very top. This high volatility was felt more intensely by superrich income earners residing in the top 0.1% income share group. Any long-term effects are not statistically relevant and therefore negligible.

To confirm robustness of our results, we incorporate alternative inequality measures, re-estimate of our baseline analyses by using an unrestricted calculation of standardized p-values, and use a different composition of predictor variables. Our results remain robust to all sensitivity analyses performed. Most notably, our results for more general income inequality measures including the Gini coefficient, the Theil's entropy index, the Atkinson index and the relative mean deviation, all report an inequality-increasing and statistically significant short-term impact stemming from Hurricane Katrina. This is additional statistical evidence that Louisiana, in a world without the Hurricane Katrina, would have experienced a less volatile and income-increasing evolution in the short-term. With consideration to our findings, we conclude that Hurricane Katrina has been identified as a strong driver of short-term income inequality and accelerator of a widening gap between the rich and the poor.

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Appendix

Table A.1: Variable definitions and sources

Variables	Definition	Source
Outcome Variables		
Inequality Measures I (shares)		
Top 0.1% Income Share	Income share accruing to the top 0.1% of earners (P99.9-100)	World Inequality Database
Next 0.9% Income Share	Income share of the earners with the highest 1% less the top 0.1% share (P99-99.9)	World Inequality Database
Top 1% Income Share	Income share accruing to the top 1% of earners (P99-100)	World Inequality Database
Next 4% Income Share	Income share of the earners with the highest 5% less the top 1% share (P95-99)	World Inequality Database
Top 5% Income Share	Income share accruing to the top 5% of earners (P95-100)	World Inequality Database
Next 9% Income Share	Income share of the earners with the highest 10% less the top 1% share (P90-99)	World Inequality Database
Top 10% Income Share	Income share accruing to the top 10% of earners (P90-100)	World Inequality Database
Bottom 90% Income Share	Income share earned by those with the 90% lowest incomes (P0-P90)	World Inequality Database
Inequality Measures II (ratios)		
Top 1% to Next 9% Ratio	Income share of the top 1% divided by income share of the next nine percentiles under the top one decile	Own Calculation based on WID
Top 1% to Bottom 90% Ratio	Income share of the top 1% divided by income share of the bottom 90%	Own Calculation based on WID
Inequality Measures III (others)		
Market Income Gini	Gini coefficient for market income inequality, pre-taxes and transfers	Frank (2014)
Atkinson Index	Atkinson index employed uses an inequality aversion parameter of 0.5, indicating higher sensitivity for changes at the top of the income distribution	Frank (2014)
Theil's Entropy Index	Theil index measures changes in inequality from reallocations of income depend only on the relative distances between individuals	Frank (2014)
Relative Mean Deviation	Relative mean deviation represents the average absolute distance between each individual's income and the mean income of the population	Frank (2014)
Average Income Measures		
Average Income Top 0.1%	Average fiscal income within the top 0.1% group measured in constant 2020 USD (ppp). It includes labour income, capital income and mixed income, before any deductions	World Inequality Database
Average Income Top 1%	Average fiscal income within the top 1% group measured in constant 2020 USD (ppp). It includes labour income, capital income and mixed income, before any deductions	World Inequality Database
Average Income Top 10%	Average fiscal income within the top 10% group measured in constant 2020 USD (ppp). It includes labour income, capital income and mixed income, before any deductions	World Inequality Database
Average Income Bottom 90%	Average fiscal income within the bottom 90% group measured in constant 2020 USD (ppp). It includes labour income, capital income and mixed income, before any deductions	World Inequality Database
Predictor Variables		
Economic Development	Personal income per capita (nominal) from wages, proprietors' income, dividends, interest, rents, and government benefits, logarithmized	Bureau of Economic Analysis
Population	Total midyear population	Bureau of Economic Analysis
Employment	Total number of full- and part-time jobs	Bureau of Economic Analysis
High School Attainment	Population share with at least a high school degree	Frank (2009)
College Attainment	Population share with at least a college degree	Frank (2009)
Economic Freedom Subindices		
a) Government Spending	Subindex for government spending evaluated in terms of economic freedom	Fraser Institute
b) Taxation	Subindex for tax regulations evaluated in terms of economic freedom	Fraser Institute
c) Labor Market Regulation	Subindex for labor market regulations evaluated in terms of economic freedom	Fraser Institute

Table A.2: Donor pool states and share to construct synthetic Louisiana

State	Weight									
	Top 5%	Top 10%	Next 0.9%	Next 4%	T01/N09	T10/B90	Gini	Atkinson	Theil	RMD
Alaska	0	0	0	0	0	0	0.076	0	0.124	0.080
Arizona	0	0	0	0	0	0	0	0	0	0
Arkansas	0.104	0	0.143	0	0	0	0.276	0.079	0	0
California	0	0	0	0	0	0	0	0	0	0
Colorado	0	0	0	0	0	0	0	0	0	0
Connecticut	0	0	0	0	0	0	0	0	0	0
Delaware	0	0	0	0	0	0	0	0	0	0
Georgia	0	0	0	0.054	0	0	0	0	0	0
Hawaii	0	0	0	0	0	0	0	0	0	0
Idaho	0	0	0	0	0	0	0	0	0	0
Illinois	0	0	0	0	0	0	0	0	0	0
Iowa	0	0	0	0	0	0	0	0	0	0
Kansas	0	0	0	0	0	0	0	0	0	0
Kentucky	0	0.060	0	0	0.264	0	0	0.415	0.324	0
Maine	0	0	0	0	0	0	0	0	0	0
Maryland	0	0	0	0	0	0	0	0	0	0
Massachusetts	0	0	0	0	0	0	0	0	0	0
Michigan	0	0	0	0	0	0	0	0	0	0
Minnesota	0	0	0	0	0	0	0	0	0	0
Missouri	0	0	0	0	0	0	0	0	0	0
Nebraska	0	0	0	0	0	0	0	0	0	0
Nevada	0	0	0	0	0	0	0	0	0	0
New Hampshire	0	0	0	0	0	0	0	0	0	0
New Jersey	0	0	0	0	0	0	0	0	0	0
New Mexico	0	0	0	0	0	0	0.183	0.136	0	0.179
New York	0	0	0.036	0	0	0	0	0	0	0
North Carolina	0	0	0	0	0	0	0	0	0	0
North Dakota	0	0	0	0	0	0	0	0	0	0
Ohio	0	0	0	0	0	0.108	0	0	0	0
Oklahoma	0	0	0	0	0	0	0	0	0	0
Oregon	0	0	0	0	0	0	0	0	0	0
Pennsylvania	0	0	0	0	0	0	0	0	0	0
Rhode Island	0	0	0	0	0	0	0	0	0	0
South Carolina	0	0	0	0	0	0	0	0	0	0
South Dakota	0	0	0	0	0	0	0	0	0	0
Tennessee	0.244	0.436	0.649	0.397	0.265	0.236	0	0.084	0.076	0
Texas	0.248	0.143	0.076	0.028	0.108	0.180	0.378	0.285	0.319	0.462
Utah	0	0	0	0	0	0	0	0	0	0
Vermont	0	0	0	0	0	0	0	0	0	0
Virginia	0	0	0	0	0	0	0	0	0	0
Washington	0	0	0	0	0	0	0	0	0	0
West Virginia	0.405	0.361	0.287	0.386	0.363	0.476	0.162	0	0.157	0.279
Wisconsin	0	0	0	0	0	0	0	0	0	0
Wyoming	0	0	0	0	0	0	0	0	0	0

Table A.3: Synthetic Louisiana predictor weights: Alternative inequality measures

Variables	Top 5% Synthetic	Top 10% Synthetic	Next 0.9% Synthetic	Next 4% Synthetic	T01/N09 Synthetic	T10/B90 Synthetic	Gini Synthetic	Atkinson Synthetic	Theil Synthetic	RMD Synthetic
Top 5% Income Share	0.0489									
Top 10% Income Share		0.3584								
Next 0.9% Income Share			0.0204							
Next 4% Income Share				0.1911						
T01/N09 Ratio					0.1439					
T10/B90 Ratio						0.0012				
Gini Coefficient							0.0821			
Atkinson Index								0.0173		
Theil's Entropy Index									0.1205	
Relative Mean Deviation										0.0887
Log Income per capita	0.1846	0.0673	0.0234	0.0207	0.5842	0.0235	0.0103	0.0013	0.0004	0.0001
Log Population	0.1934	0.0003	0.1273	0.1932	0.0234	0.1218	0.8367	0.9464	0.4702	0.9028
Log Employment	0.5325	0.5161	0.8174	0.4817	0.0442	0.6097	0.0532	0.0200	0.1692	0.0057
ECF Taxation	0.0030	0.0093	0.0018	0.0043	0.0149	0.0021	0.0039	0.0033	0.0348	0.0005
ECF Government Spending	0.0037	0.0019	0.0002	0.0015	0.0095	0.1828	0.0006	0.0042	0.1086	0.0013
ECF Labor Market Regulations	0.0076	0.0131	0.0026	0.0021	0.0997	0.0567	0.0039	0.0003	0.0271	0.0009
High School Attainment	0.0196	0.0232	0.0054	0.0347	0.0793	0.0000	0.0008	0.0049	0.0692	0.0000
College Attainment	0.0067	0.0105	0.0013	0.0706	0.0008	0.0023	0.0085	0.0021	0.0000	0.0000

Note: This table shows the predictor weights to create synthetic Louisiana.

Table A.4: Synthetic Louisiana predictor means: Alternative inequality measures

Variables	Louisiana	Top 5% Synthetic	Top 10% Synthetic	Next 0.9% Synthetic	Next 4% Synthetic	T01/N09 Synthetic	T10/B90 Synthetic	Gini Synthetic	Atkinson Synthetic	Theil Synthetic	RMD Synthetic
Top 5% Income Share	0.2656	0.2621									
Top 10% Income Share	0.3861		0.3858								
Next 0.9% Income Share	0.0797			0.0781							
Next 4% Income Share	0.1420				0.1414						
T01/N09 Ratio	0.5413					0.5372					
T10/B90 Ratio	0.6315						0.6245				
Gini Coefficient	0.5210							0.5202			
Atkinson Index	0.2115								0.2095		
Theil's Entropy Index	0.5135									0.4997	
Relative Mean Deviation	0.7308										0.7308
Log Income per capita	8.9935	9.0118	9.0054	9.0153	9.0018	8.9928	9.0191	9.0077	9.0640	9.0883	9.0838
Log Population	1.3966	1.3675	1.3439	1.3424	1.3688	1.2504	1.3884	1.3897	1.3954	1.3761	1.3947
Log Employment	0.6713	0.6658	0.6556	0.6750	0.6822	0.5390	0.6675	0.7279	0.7759	0.7428	0.7417
ECF Taxation	6.5370	5.9985	6.2008	6.3928	6.1304	5.9044	5.7380	6.0497	6.2259	6.1095	5.9733
ECF Government Spending	6.4551	7.1332	7.2630	7.4844	7.2310	6.9453	6.4808	7.4525	7.1271	6.7059	6.5617
ECF Labor Market Regulations	3.3642	3.6056	3.6514	3.7814	3.6692	3.4707	3.3677	3.8959	3.9671	3.8138	3.6692
High School Attainment	0.4122	0.4269	0.4257	0.4286	0.4263	0.4217	0.4336	0.4308	0.4299	0.4314	0.4395
College Attainment	0.0863	0.0823	0.0822	0.0833	0.0832	0.0804	0.0827	0.0893	0.0929	0.0901	0.0949
RMSPE	-	0.0078	0.0088	0.0031	0.0030	0.0313	0.0243	0.0106	0.0064	0.0240	0.0115

Note: This table shows the indicator variables and the average pre-Katrina inequality for observed and synthetic Louisiana.

A.5: The effect of Katrina on top income shares: Alternative inequality measures

		Top 5%			Top 10%			Next 0.9%			Next 4%			T01/N09 ratio	
Year	Effect	p-value	std p	Effect	p-value	std p	Effect	p-value	std p	Effect	p-value	std p	Effect	p-value	std p
2005	-0.007	0.684	0.632	-0.009	0.553	0.579	-0.003	0.475	0.525	-0.003	0.343	0.486	0.051	0.375	0.281
2006	0.029	0.079	0.026	0.025	0.211	0.158	0.006	0.125	0.175	-0.006	0.200	0.229	0.213	0.031	0.000
2007	-0.053	0.000	0.000	-0.065	0.000	0.000	-0.016	0.000	0.000	-0.023	0.000	0.000	-0.028	0.594	0.531
2008	0.049	0.053	0.000	0.050	0.026	0.053	0.013	0.000	0.050	-0.004	0.514	0.400	0.367	0.000	0.000
2009	-0.017	0.211	0.237	-0.013	0.395	0.395	-0.001	0.825	0.825	-0.014	0.086	0.057	0.063	0.438	0.313
2010	-0.019	0.368	0.0263	-0.021	0.289	0.237	0.000	1.000	1.000	-0.014	0.143	0.029	0.030	0.781	0.719
2011	-0.036	0.026	0.053	-0.032	0.158	0.079	-0.003	0.575	0.550	-0.013	0.086	0.057	-0.096	0.406	0.188
2012	0.005	0.789	0.737	0.009	0.605	0.553	0.008	0.150	0.175	-0.003	0.771	0.714	0.034	0.719	0.625
2013	0.009	0.658	0.658	0.013	0.605	0.523	0.005	0.325	0.375	-0.002	0.800	0.800	0.906	0.406	0.313
2014	0.000	1.000	1.000	-0.003	0.974	0.974	-0.000	0.975	0.975	-0.003	0.714	0.743	0.098	0.25	0.25
2015	-0.016	0.312	0.289	-0.020	0.316	0.289	-0.005	0.375	0.375	-0.005	0.543	0.457	-0.006	1.000	0.938
		T10/B90			Gini			Atkinson			Theil			RMD	
Year	Effect	p-value	std p	Effect	p-value	std p	Effect	p-value	std p	Effect	p-value	std p	Effect	p-value	std p
2005	-0.020	0.778	0.778	0.035	0.000	0.000	0.002	0.711	0.763	0.022	0.459	0.514	0.023	0.128	0.103
2006	0.099	0.111	0.028	0.035	0.243	0.000	0.004	0.632	0.684	0.031	0.405	0.432	0.032	0.051	0.026
2007	-0.192	0.000	0.000	0.038	0.000	0.000	0.018	0.026	0.053	0.108	0.027	0.000	0.048	0.026	0.000
2008	0.217	0.000	0.028	0.026	0.098	0.146	0.014	0.105	0.079	0.080	0.054	0.000	0.032	0.026	0.051
2009	-0.035	0.472	0.444	0.026	0.122	0.146	0.022	0.026	0.000	0.112	0.027	0.000	0.042	0.026	0.026
2010	-0.059	0.361	0.361	0.026	0.122	0.122	0.011	0.421	0.368	0.043	0.486	0.540	0.040	0.051	0.026
2011	-0.094	0.194	0.167	-0.006	0.683	0.659	-0.001	0.947	0.947	-0.039	0.595	0.595	0.002	0.872	0.872
2012	0.042	0.528	0.500	0.028	0.098	0.122	0.012	0.316	0.395	0.053	0.541	0.432	0.040	0.051	0.000
2013	0.055	0.472	0.500	0.015	0.341	0.415	0.010	0.474	0.553	0.053	0.541	0.541	0.026	0.154	0.179
2014	-0.001	1.000	1.000	0.017	0.171	0.268	0.010	0.395	0.474	0.056	0.514	0.514	0.030	0.051	0.103
2015	-0.060	0.361	0.417	0.013	0.317	0.415	-0.002	0.842	0.895	-0.020	0.811	0.811	0.020	0.282	0.231

Note: This table shows the annual treatment effects, p-values, and standardized p-values.

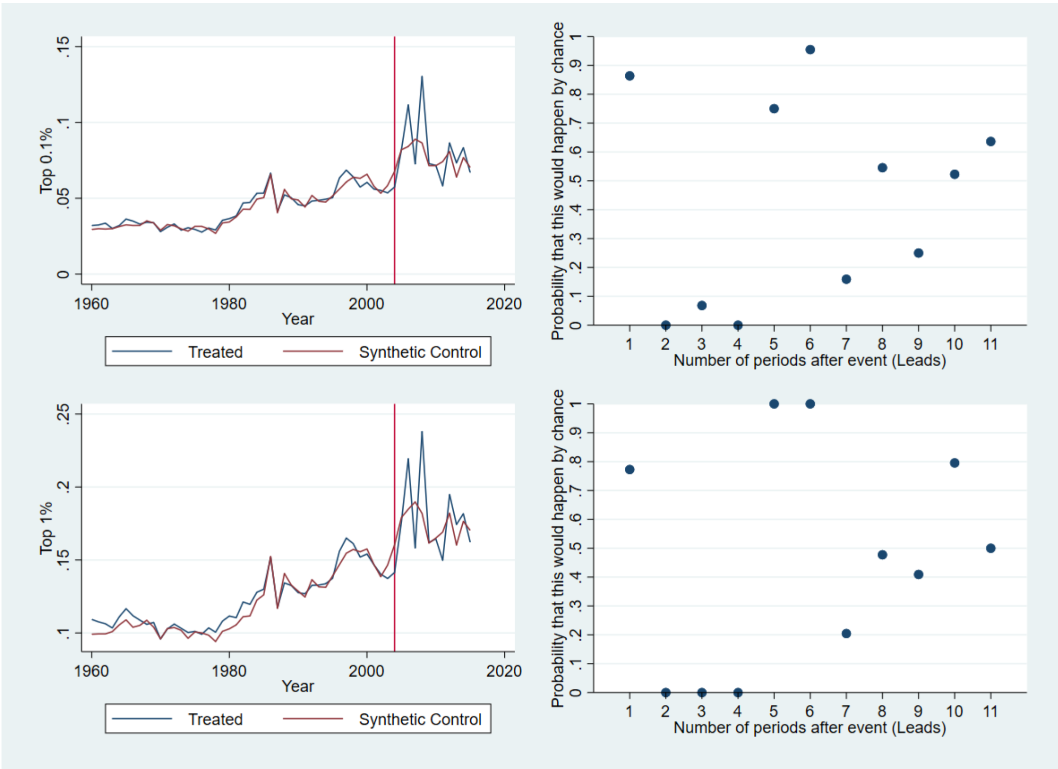

Figure A.1: The top left figure shows the trends presented in the baseline analysis for the top 0.1% income shares. The top right figure shows standardized p-values of the effect of Katrina on the top 0.1% income shares calculated using all countries in the donor pool. The top left figure shows the trends presented in the baseline analysis for the top 1% income shares. The top right figure shows standardized p-values of the effect of Katrina on the top 1% income shares calculated using all countries in the donor pool.

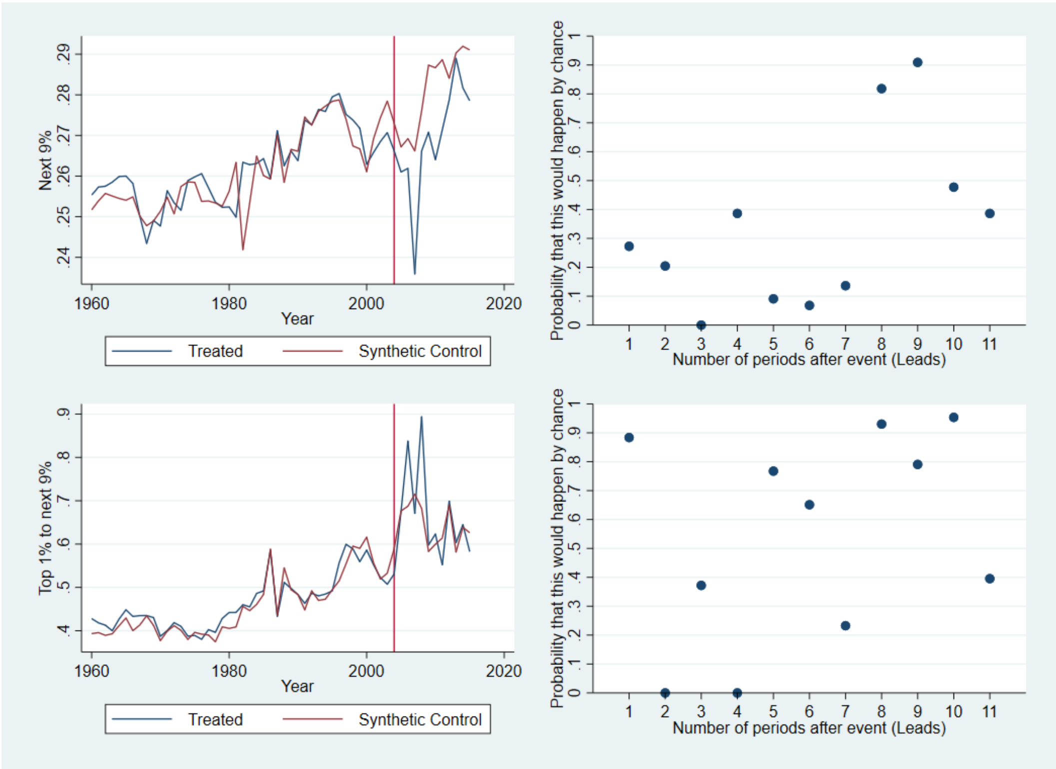

Figure A.2: The top left figure shows the trends presented in the baseline analysis for in next 9% income shares. The top right figure shows standardized p-values of the effect of Katrina on the next 9% income shares calculated using all countries in the donor pool. The top left figure shows the trends presented in the baseline analysis for the ratio between top 1% to next 9%. The top right figure shows standardized p-values calculated using all countries in the donor pool.

Table A.6: Donor pool states and share to construct synthetic Louisiana

State	Weight			
	Top 0.1%	Top 1%	Next9%	T1/N9 ratio
Alaska	0	0	0	0
Arizona	0	0	0	0
Arkansas	0	0	0	0
California	0	0	0	0
Colorado	0	0	0	0
Connecticut	0	0	0	0
Delaware	0	0	0	0
Georgia	0	0	0	0
Hawaii	0	0	0	0
Idaho	0	0	0	0
Illinois	0	0	0	0
Iowa	0	0	0	0
Kansas	0	0	0	0
Kentucky	0.024	0	0.169	0.211
Maine	0	0	0	0
Maryland	0	0	0	0
Massachusetts	0	0	0	0
Michigan	0	0	0	0
Minnesota	0	0	0	0
Missouri	0	0	0	0
Nebraska	0	0	0	0
Nevada	0	0	0	0
New Hampshire	0	0	0	0
New Jersey	0	0	0	0
New Mexico	0	0	0	0.078
New York	0	0	0	0
North Carolina	0	0	0	0
North Dakota	0	0	0	0
Ohio	0	0	0.123	0
Oklahoma	0	0	0	0
Oregon	0	0	0	0
Pennsylvania	0	0	0	0
Rhode Island	0	0	0	0
South Carolina	0	0	0	0
South Dakota	0	0	0	0
Tennessee	0.227	0.312	0.303	0.172
Texas	0.252	0.234	0.074	0.248
Utah	0	0	0	0
Vermont	0	0	0	0
Virginia	0	0	0	0
Washington	0	0	0	0
West Virginia	0.496	0.454	0.330	0.291
Wisconsin	0	0	0	0
Wyoming	0	0	0	0